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ABSTRACT

Though the practice of 'correcting for residual autocorrelation' has long been criticized it is still commonly advocated and followed. A simple example shows that even when a linear regression model has first order autoregressive errors it is possible for autoregressive least squares estimation (e.g. Cochrane-Orcutt) to yield inconsistent estimates. This dramatically illustrates that 'autocorrelation correction' is invalid in general, and cannot be justified on the grounds of 'robustifying' estimation against the presence of residual serial correlation. Invalid common factors in I(1) systems also have adverse effects on inference. A 'general-to-specific' modelling strategy applied to the observed modelled variables avoids these difficulties.

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1 Introduction

It is well known that the presence of serial correlation in the errors of a linear regression model induces problems for inference based solely on OLS methods. At the least, the OLS coefficient estimators will be inefficient and the corresponding standard errors incorrect, thus invalidating the conventional use of test statistics based on them. More seriously the OLS estimators will be biased and inconsistent in dynamic regression models. Hence it is important in econometric modelling to use residuals to test for the absence of serial correlation in the model errors. This is achieved easily now via the many test statistics which are included in econometrics and statistics software (e.g. those of Durbin and Watson (1950, 1951), Durbin (1970), and the more recent ones such as Breusch (1978) and Godfrey (1978), each of which are described in Engle (1984) and Godfrey (1990)). Indeed, it is now rare to find a piece of empirical economics using time series data that does not include a test for serial correlation. However, if the null hypothesis of no serial correlation is rejected there is not a unique alternative model to adopt, since all the test result has established is that the present model is inadequate, probably by having an inappropriate dynamic specification. Nevertheless, it remains a common practice to 'autocorrelation correct' the model by re-estimating it using one of the methods that assumes that the errors are generated by an autoregressive process e.g. by methods based on Cochrane-Orcutt (1949). This procedure has sometimes been justified on the grounds that, (i) it provides parameter estimates that are 'robust' to autocorrelated errors, and (ii) that it is appropriate to modify the original model in the direction of the alternative for which the test statistics used have high power. Neither of these putative justifications is valid in general, as has been argued by Sargan (1964, 1980), and *inter alia* Hendry and Mizon (1978), Hoover (1988), and Spanos (1988), and as the example in the next section dramatically illustrates.

The next section describes a bivariate process which has been used in PC-NAIVE [see Hendry, Neale and Ericsson (1990)] to generate a sample of size 100 to demonstrate that even when the regression error term is first order autoregressive, Autoregressive Least Squares (ALS) estimation yields an **inconsistent** estimator of the regression coefficient. 'Autocorrelation correction' is one example of methods used in a 'specific-to-general' modelling strategy, which has been criticized by *inter alia* Mizon (1977a,b), Hendry (1983, 1987), and Hendry and Mizon (1990). The alternative strategy of following a general-to-specific approach to modelling avoids these problems, and is shown to work well for this example. In doing this the properties of the ALS estimator are compared with those of OLS estimators of the parameters of alternative models, and the encompassing abilities of these models are evaluated. In order to be sure that the results obtained using a single artificially generated sample are not overly peculiar to that sample, and also to assess the relevance of limiting distribution theory concerning the properties of the sample statistics used, results from a Monte Carlo simulation involving 10,000 replications are summarized. In view of the serious disadvantages that result from incorrectly imposing common factor restrictions section 3 contains an analysis of the structure of a linear stationary ergodic dynamic process, a characterization of the common factor restrictions, and discussion of some sufficient conditions for the common factor restrictions to hold. These sufficient conditions reveal that common factor restrictions are unlikely to be valid in general. An exception is the case in which the order of dynamics specified in a model is too large, so that the common factors correspond to zero roots. Section 4 demonstrates that difficulties also arise in the analysis of integrated variables when common factor restrictions are incorrectly imposed. These and other conclusions are contained in section 5.

2 'Autocorrelation Correction' Can Yield Inconsistent Estimates: A Simple Example.

An important part of designing econometric time series models to be congruent with the available information is to ensure that the class of model used is coherent with the time series properties of the sample data (see Hendry (1987), Hendry and Mizon (1990)). In order to illustrate the adverse consequences of not doing so Mizon (1993) used PC-NAIVE to generate data from the following data generating process (DGP):

$$\begin{aligned} y_t &= \alpha y_{t-1} + \epsilon_t \\ z_t &= \eta_t \end{aligned} \tag{1}$$

with

$$\begin{pmatrix} \epsilon_t \\ \eta_t \end{pmatrix} \sim \mathsf{NI}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\epsilon^2 & \rho \\ \rho & \sigma_\eta^2 \end{pmatrix} \right) \tag{2}$$

when $\sigma_\epsilon^2 = \sigma_\eta^2 = 1,\ \alpha = 0.5,\ \rho = 0.9$, and the econometric sample size $T = 100$. This DGP was chosen so that y_t is serially dependent, and z_t is serially independent, but they are correlated with each other. As a result the static linear regression model M_1 :

$$y_t = \beta_1 z_t + u_{1t} \tag{3}$$

which relates y_t to z_t only, cannot be congruent since the error term u_{1t} must be serially correlated. This implies that u_{1t} contains valuable information for the modelling of y_t, namely lagged values of y in this case. In fact, although the OLS estimator $\hat{\beta}_1$ is consistent for β, it is inefficient and the OLS standard errors are incorrect. This is illustrated by the following results, obtained from estimating M_1 for the data from replication 1000 of a Monte Carlo simulation run on PC-NAIVE using the DGP above[1]. The full sample OLS estimates for the regression model M_1, with a constant term c_1 included, are:

$$\begin{array}{ccccc} \hat{y}_t & = & -0.059 & + & 1.025\, z_t \\ & & [0.079] & & [0.074] \\ R^2 = 0.619 & & \hat{\sigma}_1 = 0.794 & & DW = 0.915 \end{array} \tag{4}$$

The figures in square brackets are heteroscedastic consistent standard errors, which nonetheless are inappropriate because of the residual serial correlation indicated by the DW statistic, and the F form of the Lagrange multiplier first order serial correlation test statistic which has the value $F(1,97) = 40.54$. However, as judged by a wide variety of other diagnostic test statistics there appear to be no further seri-

[1]Should anyone wish to reproduce these results the seed used for the random number generator was 980.

ous misspecifications. For example: ARCH(1,96) = 1.590 (with a p-value of 0.21), Reset(1,97) = 1.913 (with a p-value of 0.17), normality $\chi^2(2) = 0.343$, and the parameter constancy test statistics of Hansen (1991) based on the backward cumulative scores do not reject the hypothesis that σ_1^2 is constant (the variance instability test statistic = 0.157), or the hypothesis that σ_1^2 and β_1 are constant (the joint instability test statistic = 0.728).

Mizon (1993) was concerned solely with an illustration of the consequences of using a noncongruent model. The emphasis in this paper is on the relative merits of alternative modelling strategies for responding to the finding that residuals are serially correlated. In particular, a comparison is made between, 'autocorrelation correction' until residuals appear to be white noise; robustification via semiparametric estimation; and the alternative of recommencing modelling by finding a congruent general model and then testing down using a general-to-specific strategy. Note that an important distinction between these procedures is that the first two adopt alternative estimation methods for a given model, whilst the third one embodies a modelling strategy which aims to find the simplest economically interpretable model that is congruent with the available information.

The precise nature of the serial correlation in u_{1t} is readily seen by adopting a reparameterization of equations (1) and (2). The distribution underlying (1) and (2) is $\mathsf{D}(y_t, z_t | y_{t-1}, z_{t-1}; \boldsymbol{\theta})$ with $\boldsymbol{\theta}' = \left(\alpha, \rho, \sigma_\epsilon^2, \sigma_\eta^2\right)$, which can be reparameterized as $\mathsf{D}(y_t | z_t, y_{t-1}, z_{t-1}; \boldsymbol{\theta}_1) \times \mathsf{D}(z_t | y_{t-1}, z_{t-1}; \boldsymbol{\theta}_2)$ when $\boldsymbol{\theta}_1' = (\alpha, \beta, \sigma_\nu^2)$ and $\boldsymbol{\theta}_2 = \left(\sigma_\eta^2\right)$ with $\beta = \rho/\sigma_\eta^2$, and $\sigma_\nu^2 = \sigma_\epsilon^2 - \beta^2\sigma_\eta^2$:

$$\begin{aligned} y_t &= \beta z_t + \alpha y_{t-1} + \nu_t \\ z_t &= \eta_t \end{aligned} \tag{5}$$

$$\begin{pmatrix} \nu_t \\ \eta_t \end{pmatrix} \sim \mathsf{NI}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\nu^2 & 0 \\ 0 & \sigma_\eta^2 \end{pmatrix} \right) \tag{6}$$

Hence comparison of M_1 with (5) and (6) reveals that the population value of β_1 is β, and that the error term in M_1 has the form $u_{1t} = \alpha y_{t-1} + \nu_t$ which is serially correlated via y_{t-1}. The important question then is how in practice to respond to the indication of serially correlated errors for M_1.

2.1 Autocorrelation Correction.

A common next step is to re-estimate M_1 assuming that the process generating the error u_{1t} is first order autoregressive. This is particularly the case if the parameter of interest is the partial response of y_t to z_t, without being too careful about the specification of the information set relative to which this response is partial. Recent textbooks that present this approach as an appropriate reaction include: Berndt (1991, pp. 92, 281-2, 497, 567), Greene (1991, pp. 432-3), and Griffiths *et al* (1993, p536). On the other hand, Spanos (1986, pp.507-511) and Davidson and MacKinnon (1993, pp.364-369) are recent textbooks that clearly mention the dangers of imposing invalid common factor restrictions. The procedure of modifying the estimation method until the residuals appear to be white noise, is illustrated here by the following first order Autoregressive Least Squares (ALS(1)) estimates:

$$\begin{array}{rccc} \hat{y}_t = & -0.066 & +0.741 z_t & +0.707 \hat{u}_{1t-1} \\ & (0.207) & (0.053) & (0.073) \end{array} \tag{7}$$

Although the equation standard error $\hat{\sigma}_2 = 0.602$ shows an improvement relative to the OLS estimates of M_1, the ARCH(1) test statistic $F\,(1,95) = 0.369$ (p-value 0.545) and the Jarque-Bera (1980) normality test statistic $\chi^2\,(2) = 1.131$ indicate no apparent misspecification, the White (1980) heteroscedasticity test statistic calculated as $F\,(2,94) = 4.341$ (p-value 0.016) indicates a problem. Further, the residual correlogram suggests that there might be still some serial correlation in the residuals at lags 1, 4 and 5 - an $F(5,88) = 2.289$ (p-value 0.053) confirms that the hypothesis of the first five residual serial correlation coefficients being zero is not well supported.

More importantly, the point estimate of the coefficient of z_t at 0.741 is a long way from the population value of $\beta = 0.9$, and that of $\hat{u}_{1t-1}$ at 0.707 a poor estimate of $\alpha = 0.5$. Indeed, this ALS(1) estimator is biased and inconsistent for both α and β in the context of the DGP given by (1) and (2). This can be seen by noting that on convergence the ALS(1) estimators of α and β will (as a consequence of the biquadratic nature of the estimation criterion function - see Sargan (1964)) satisfy the following first order conditions simultaneously:

$$\hat{\alpha}_2 = \sum_{t=1}^{T} (y_t - \hat{\beta}_2 z_t)(y_{t-1} - \hat{\beta}_2 z_{t-1}) / \sum_{t=1}^{T} (y_{t-1} - \hat{\beta}_2 z_{t-1})^2 \tag{8}$$

$$\hat{\beta}_2 = \sum_{t=1}^{T}(y_t - \hat{\alpha}_2 y_{t-1})(z_t - \hat{\alpha}_2 z_{t-1}) / \sum_{t=1}^{T}(z_t - \hat{\alpha}_2 z_{t-1})^2 \tag{9}$$

Hence denoting the pseudo true values of $\hat{\alpha}_2$ and $\hat{\beta}_2$ by α^* and β^* respectively, and noting that from (5) and (6):

$$(y_t - \beta^* z_t) = (\beta - \beta^*)z_t + \alpha y_{t-1} + \nu_t \tag{10}$$

$$(y_t - \alpha^* y_{t-1}) = \beta z_t + (\alpha - \alpha^*)y_{t-1} + \nu_t \tag{11}$$

it follows that α^* and β^* must simultaneously satisfy:

$$\alpha^* = \alpha - \alpha\beta^*(\beta^* - \beta)/[\beta^{*2} - 2\beta\beta^* + \sigma_\epsilon^2/(1-\alpha^2)\sigma_\eta^2] \tag{12}$$

$$\beta^* = \beta - \alpha\beta\alpha^*/(1 + \alpha^{*2}) \tag{13}$$

Note that if $\alpha^* = \alpha$ then provided that $\alpha \neq 0$ (12) implies that $\beta^* = \beta$, but this is not a solution of (13) if $\beta \neq 0$. Equally, if $\beta^* = \beta$ then (12) implies that $\alpha = \alpha^*$, but this is only consistent with (13) if $\alpha = \alpha^* = 0$. Hence whenever $\alpha \neq 0$ ALS(1) is inconsistent for both α and β. For the particular values of α, β, σ_ϵ^2 and σ_η^2 in the DGP given by (1) and (2) the real solutions of (12) and (13) are $\alpha^* = 0.625$ and $\beta^* = 0.698$ to three decimal places.[2]

The 'autocorrelation corrector' may, having noted the fact that the residuals still appear to be serially correlated, re-estimate M_1 allowing for second order autoregressive errors. Doing so yields the following results:

$$\begin{array}{rcllll} y_t & = & -0.056 & +0.699 z_t & +0.912\hat{u}_{1t-1} & -0.274\hat{u}_{1t-2} \\ & & (0.164) & (0.047) & (0.101) & (0.102) \end{array} \tag{14}$$

which has an equation standard error of $\hat{\sigma}_{AR2}$= 0.587 that appears to be a marginal improvement in goodness of fit relative to equation (7). Inspection of the residual correlogram for the ALS(2) estimates reveals no serious evidence of further serial

[2]In fact, substitution of (13) in (12) yields a 5^{th} order polynomial in α^* which has the following roots as solutions: $0.045 \pm 1.263, -0.108 \pm 0.700, 0.625$ with $0.755 \pm 0.931, 1.147 \pm 0.532, 0.698$ the corresponding solutions for β^*.

correlation, and the ARCH, normality and parameter constancy test statistics yield no evidence of misspecification. In fact, had the 'autocorrelation corrector' continued as far as a fifth order autoregressive error process for u_{1t}, the resulting ALS estimates would have revealed no need for autocorrelation correction beyond the second order. The statistics for testing the order of the autoregressive error process in Table 1 substantiate this point.

Table 1: Test Statistics for AR errors.[3]

Order of AR Errors		Number of Common Factors	
Hypothesis	$\chi^2(1)$	Hypothesis	$\chi^2(1)$
$AR(4):AR(5)$	2.524	$r=1$	0.129
$AR(3):AR(4)$	0.054	$r=2$	0.250
$AR(2):AR(3)$	1.288	$r=3$	0.645
$AR(1):AR(2)$	5.424	$r=4$	3.537
$AR(0):AR(1)$	49.99	$r=5$	65.63

The results given in the left hand side of Table 1 are likelihood ratio test statistics for hypotheses about the order of autoregressive error process AR(i-1) versus AR(i) for i=1,2,...5. Under the null hypothesis each of these test statistics has a limiting $\chi^2(1)$ distribution. The conclusion from this sequence of tests is that if M_1 is estimated by ALS then the order of autoregressive process needed is no larger than 2. The estimated roots of the AR(2) polynomial are $0.456 \pm 0.132i$, and the fact that they are complex may well be the reason for the rejection of the hypothesis that the order of the AR polynomial can be reduced to 1, given that common factors are imposed. Hence the 'autocorrelation corrector' after estimating M_1 by ALS(2), which results in the residuals appearing to be white noise, may believe that the estimated partial response of y_t to z_t at 0.699 is reliable, especially if there is no other conventional indication of model misspecification. However, this estimated coefficient of z_t at 0.699 (with a standard error of 0.047) is a long way off $\beta = 0.9$! The strategy of whitening the residuals by introducing higher and higher orders of residual autocorrelation

[3] These statistics were produced using PC-GIVE version 7 [see Doornik and Hendry (1992)].

correction has failed to yield a consistent estimator of β, as it always will unless the implied common factor restrictions are satisfied.

The hypothesized behaviour of the 'autocorrelation corrector' above is an example of a series of moves from a specific to a more general model in response to indications of model misspecification. The sequence began with OLS estimation of M_1, and was followed by ALS(1), ALS(2) *etc.* of M_1. In this particular case had the sequence of estimation and testing started from the model involving a fifth order autocorrelated error process and moved down to non-rejected lower orders, the selected model would still have been M_1 with AR(2) errors. Notice though, that the 'autocorrelation corrector' would have imposed common factor restrictions throughout, independently of their validity! The inappropriateness of M_1 with any order of autoregressive errors, will only be revealed if the common factor restrictions are tested.

The results given on the right hand side of Table 1 are incremental Wald test statistics for the hypothesis that M_1, augmented by 5 lags of y and z, has r common factors for $r = 1, 2, ...5$. Under the null hypothesis each of these test statistics has a limiting $\chi^2(1)$ distribution. The conclusion from this sequence of ordered tests is that there are 4 common factors. However, if following this conclusion M_4 (see (15) below) were estimated by ALS(4) (this maintains 5 lags in the model, but with 4 common factors) the results would reveal that all 4 estimated serial correlation coefficients are not significantly different from zero. Thus, all 4 roots of the fourth order common factor polynomial are zero, which is not surprising given that M_3 (see (15) is the DGP. This provides an illustration of there being valid common factor restrictions as a result of common factors with zero roots being able to represent a model which contains redundant lags of all variables.

2.2 Semiparametric Adjustment/Estimation.

Another approach to the estimation of the response of y_t to z_t involves a mixture of parametric and nonparametric estimation, in which the OLS point estimate of β and a heteroscedastic and autocorrelation consistent (HAC) estimator of its variance are calculated. Andrews (1991) and Newey and West (1987) *inter alia* propose and discuss alternative HAC estimators. Since the OLS estimator $\hat{\beta}_1$ is consistent for

β this "semiparametric" approach could be expected to achieve robust inference on the short run response of y_t to z_t. A GAUSS programme was written implementing covariance matrix estimators discussed in Andrews (1991), and HAC estimates using four alternative kernels, and bandwidths in the range 1.0 to 10.0 $\left(=\sqrt{T}\right)$, were generated. The results for a bandwidth of 1.0 are are given in Table 2.

Table 2: Alternative Heteroscedastic-Autocorrelation Consistent Estimates of $SE\left(\hat{\beta}_1\right)$.

HAC Estimates

kernel	$SE\left(\hat{\beta}_1\right)$
truncated	0.0741
Bartlett	0.0742
Parzen	0.1049
Tukey-Hanning	0.0742

In this case the HAC estimates are (with the exception of that from the Parzen kernel) very close to the population, sample, and Monte Carlo estimates using the standard OLS formula $V_{ols}\left(\hat{\beta}_1\right) = \sigma_1^2 (X'X)^{-1}$ - see Table 3. However, the standard OLS formula is incorrect in this case, and should be replaced by $V\left(\hat{\beta}_1\right) = \sigma_1^2 (X'X)^{-1} X'AX (X'X)^{-1}$ when $A = (a_{ij})$ with $a_{ij} = \alpha^{|i-j|}$ for $i, j = 1, 2.....T$. For the sample data X generated by replication 1000 of the PC-NAIVE run, and the population parameter values $\alpha = 0.5$ and $\sigma_1^2 = 0.5233$, $V\left(\hat{\beta}_1\right) = 0.0061$ thus giving an estimated true standard error of $SE\left(\hat{\beta}_1\right) = 0.0784$. Hence the semiparametric approach appears to be of limited value in this particular case where the essential problem with M_1 is that u_{1t} is not an innovation with respect to y_{t-1}, z_t and z_{t-1}. Indeed, this approach lacks efficiency in general, and yields no information about the difference between the long run and short run responses of y to z.

2.3 General-to-Specific Modelling.

An alternative strategy to either, attempting to "patch up" M_1 in a specific-to-general modelling strategy, or to using semiparametric estimation of M_1, is to acknowledge the inadequacy of M_1 and begin modelling again. This requires that a congruent general model be found, within which it will then be valid to test the parsimonious encompassing hypotheses for acceptable simplifications of it. Some of the models relevant in the present context are:

$$
\begin{aligned}
&\mathsf{M}_1 \quad y_t = \beta_1 z_t + u_{1t} \\
&\mathsf{M}_2 \quad y_t = \beta_2 z_t + \alpha_2 u_{1t-1} + \epsilon_{2t} \\
&\mathsf{M}_3 \quad y_t = \beta_3 z_t + \alpha_3 y_{t-1} + u_{3t} \\
&\mathsf{M}_4 \quad y_t = \beta_4 z_t + \alpha_4 y_{t-1} + \gamma_4 z_{t-1} + u_{4t}
\end{aligned}
\tag{15}
$$

Note that the scalars α, β, and γ are used for the coefficients of y_{t-1}(or u_{t-1}), z_t, and z_{t-1} respectively, with β_i the coefficient of z_t in M_i etc.. In addition, note that the most general model is M_4, so that if it is congruent it will be valid to test the ability of the remaining models to parsimoniously encompass it. To aid the understanding of these tests the population pseudo true values of the principal statistics associated with OLS estimation (ALS(1) for M_2) of these models have been calculated using the following formulae, and are given in Table 3. For the generic linear regression model $\mathbf{y} = X\boldsymbol{\beta} + \mathbf{u} = X\mathbf{b} + \mathbf{e}$ with $\mathbf{b} = (X'X)^{-1} X'\mathbf{y}$ the OLS estimator the population values were calculated as:

$$
\begin{aligned}
\tilde{\boldsymbol{\beta}} &= \mathsf{plim}_{T\to\infty}\, \mathbf{b}, \\
R\tilde{S}S &= T \ \mathsf{plim}_{T\to\infty} \left(\mathbf{e}'\mathbf{e}/T\right) = T\left(V(y) - \tilde{\boldsymbol{\beta}}' V(\mathbf{x}) \tilde{\boldsymbol{\beta}}\right), \\
\varphi &= \mathsf{plim}_{T\to\infty} \left(\mathbf{e}'\mathbf{e}_{-1}/\mathbf{e}'\mathbf{e}\right), \\
D\tilde{W} &= \mathsf{plim}_{T\to\infty}\, DW = 2\left(1-\varphi\right), \\
\tilde{\sigma}^2 &= R\tilde{S}S/\left(T-k\right), \text{ and } S\tilde{E}\left(\beta_i\right) = \tilde{\sigma}\sqrt{\{[V(\mathbf{x})]_{ii}^{-1}\}},
\end{aligned}
$$

when $V(y)$ is the variance of y, and $V(\mathbf{x})$ is the variance-covariance matrix for $\mathbf{x}$. Note that for M_2 the formula used for the calculation of the limiting variance-covariance matrix, and hence $S\tilde{E}(\beta_2)$, was that relevant for a misspecified model $(I^{-1}JI^{-1})$ when I is the information matrix and J is the variance-covariance matrix of the score vector. In general $\tilde{\sigma}^2$ and $S\tilde{E}(\beta_i)$ calculated as defined above are calibrated for a sample of size T.

Table 3: Model Characteristics.

	β_i	$SE(\hat{\beta}_i)$	α_i	$SE(\hat{\alpha}_i)$	γ_i	$SE(\hat{\gamma}_i)$	DW	σ_i
M_1								
P	0.9	0.073	0	na	0	na	1.0	0.723
S	1.025	0.074	0	na	0	na	0.92	0.794
MC	0.893	0.072	0	na	0	na	1.03	0.714
M_2								
P	0.698	0.053	0.625	0.084	0	na	1.84	0.586
S	0.741	0.053	0.707	0.073	0	na	na	0.602
MC	0.700	0.051	0.603	0.078	0	na	1.81	0.583
M_3								
P	0.9	0.044	0.5	0.038	0	na	2.0	0.436
S	0.952	0.045	0.516	0.035	0	na	1.81	0.442
MC	0.900	0.044	0.495	0.039	0	na	2.0	0.436
M_4								
P	0.9	0.044	0.5	0.060	0.0	0.070	2.0	0.436
S	0.952	0.046	0.548	0.057	−0.05	0.074	1.85	0.445
MC	0.900	0.044	0.487	0.063	0.011	0.071	1.99	0.436

The rows labelled P, S and MC report respectively the population value, the sample estimate based on the data for replication 1000 from PC-NAIVE, and the average value over 10,000 replications, for the parameter/statistic heading each column. The sample estimates were obtained using PC-GIVE version 7 [see Doornik and Hendry (1992)]. The Monte Carlo simulation results for M_1, M_3, and M_4 were generated using PC-NAIVE, and those for M_2 using GAUSS. In generating the sample and Monte Carlo statistics intercepts were included in the regressions even though their population values are all zero. The estimates are not reported since none of the point estimates exceeded 0.001 and the smallest standard error was 0.04. In the Monte Carlo study the following rejection frequencies were obtained for the t statistics for the hypotheses: (i) $\beta = 0$, 100%; (ii) $\alpha = 0$, 100%; (iii) $\alpha = 0.5$, $\simeq$5%; (iv) $\gamma = 0$, 100%.

Inspection of these population values reveals that OLS estimation applied to M_4 and M_3 yields consistent estimators of α and β, and that M_1 yields a consistent estimator of β. However, M_1 is variance dominated by the other models, and so it cannot encompass them. In addition, M_1 has serially correlated errors as noted above and indicated by the population value of the DW statistic. Although models M_3 and M_4 each yield consistent estimators of α and β, and have population values of the DW statistic equal to 2.0, M_3 is the more efficient estimator. Whilst this is not surprising given that M_3 corresponds to the DGP defined in (1) and (2), it is only in the estimation of α that the efficiency gains are noticeable. Indeed, z_t is strongly exogenous for β in both M_3 and M_4.[4]

In order to assess the congruence of each of these models in the sample Table 3 provides coefficient estimates and other statistics, using the data from replication 1000. Test statistics for ARCH(1), heteroscedasticity, normality, and functional form were also calculated for all four models, but are not reported since none was significant at conventional levels. The static long run response of y to z, which in the DGP is given by $\beta/(1-\alpha)$, has a population value of 1.8. Models M_1 and M_2 restrict the long and short run responses to be equal, as a result of imposing common factor restrictions, and so yield bad point estimates of these responses.

2.3.1 Direct Reductions of M_4.

M_4, the most general model considered in Table 3, appears to be a congruent model on the basis of all the diagnostic test statistics calculated. It is therefore relevant, and valid to test for acceptable reductions of it. Statistics for testing the hypotheses that the other three models parsimoniously encompass M_4 are given in Figure 1, which also diagrammatically presents the relationship between the models.

[4]In fact, $\mathsf{E}[u_{3t}z_t] = \mathsf{E}[u_{4t}z_t] = \mathsf{E}[\nu_t z_t] = 0$ and y_t does not Granger-cause z_t so that z_t is strongly exogenous for α, β and the error variances in both M_3 (the DGP) and M_4–see Engle, Hendry and Richard (1983). However, z_t is not even weakly exogenous for α, β and $\sigma^2_{\epsilon_2}$ in M_2, or for β and σ^2_1 in M_1. This is reflected in the fact that ALS estimation of M_2 is inconsistent for α and β, and OLS estimation of M_1 is inconsistent for α and σ^2_1, and inefficient though consistent for β .

$$M_4: \; y_t = \alpha y_{t-1} + \beta z_t + \gamma z_{t-1} + \nu_t = \alpha y_{t-1} + \beta [\, z_t - \alpha z_{t-1}] + [\, \gamma + \alpha\beta] z_{t-1} + \nu_t$$

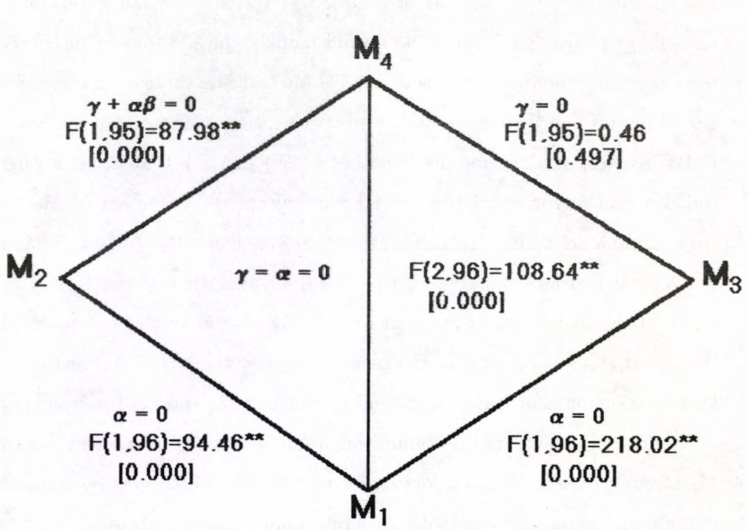

Figure 1: Parsimonious Encompassing Test Statistics

The test statistics in Figure 1 were evaluated using the data from replication 1000 of the PC-NAIVE simulation study of the data generation process defined in (1) and (2). Also note that since the models considered are dynamic all the reported $F(n_1,n_2)$ statistics only have the F distribution asymptotically. Further, note that p-values are reported in square brackets below each test statistic, and ** denotes that the test statistic rejects the null hypothesis at conventional significance levels.

The test statistics for the hypothesis that each of the models nested within M_4 parsimoniously encompass it, show that the only non-rejected reduction of M_4 is M_3 i.e. $\mathsf{M}_2\mathcal{E}_p\mathsf{M}_4$ and $\mathsf{M}_1\mathcal{E}_p\mathsf{M}_4$ are rejected but $\mathsf{M}_3\mathcal{E}_p\mathsf{M}_4$ is accepted. This result is both predictable from analysis of alternative parameterizations of the underlying DGP, and reassuring in that the use of sample test statistics within a general-to-specific modelling strategy can reveal the invalid models. In addition to the encompassing tests revealing the inadequacies of models M_1 and M_2, the parameter estimates and test statistics point to the probable misspecification of these models. Note that the COMFAC test statistic for the hypothesis $(\gamma_4 + \alpha_4\beta_4) = 0$ at 87.98 strongly rejects the common factor restriction, and hence rejects the reduction of M_4 to a static regression model with a first order autoregressive error - M_2. In fact, in M_4 the y_t lag polynomial had an estimated root of 0.548, whereas that of the z_t polynomial was 0.053. There is no lack of power in the COMFAC test in this example! Manifestly though, if $(\gamma_4 + \alpha_4\beta_4) \simeq 0$ in the population then the COMFAC test is unlikely to lead to rejection. For the DGP given by equations (1) and (2) $(\gamma_4 + \alpha_4\beta_4) = 0.45$.

Hence performing the encompassing tests within the congruent general model M_4 strongly rejects a static regression model with autoregressive error M_2, even though $u_{1t} = \alpha u_{1t-1} + w_t$ with w_t white noise! Note that $u_{1t} = \alpha y_{t-1} + \nu_t$ implies that $w_t = \alpha\beta z_{t-1} + \nu_t$ so that w_t is white noise since z_{t-1} and ν_t are mutually and serially uncorrelated, and has variance $\sigma_w^2 = \sigma_v^2 + \alpha^2\beta^2\sigma_\eta^2 = 0.393$. However, $\mathsf{E}\left[(z_t - \alpha z_{t-1})\, w_t\right] = -\alpha^2\beta\sigma_\eta^2 \neq 0$ and so even if α were known, and the quasi-differences $\tilde{y}_t = (y_t - \alpha y_{t-1})$ and $\tilde{z}_t = (z_t - \alpha z_{t-1})$ thus calculable, the Generalized Least Squares (GLS) estimator of β in M_1 would be inconsistent.

Further insight can be obtained by reparameterizing M_2 as:

$$\mathsf{M}_2 : (y_t - \alpha^* y_{t-1}) = \beta^* (z_t - \alpha^* z_{t-1}) + \zeta_t \tag{16}$$

in which

$$\zeta_t = \nu_t + (\alpha - \alpha^*)y_{t-1} + (\beta - \beta^*)z_t + \alpha^*\beta^* z_{t-1} \tag{17}$$

so that

$$\begin{aligned}\sigma_\zeta^2 &= (1 - 2\alpha\alpha^* + \alpha^{*^2})V(y) + [\beta^{*^2}(1 + \alpha^{*^2}) - 2\beta\beta^*(1 - \alpha\alpha^* + \alpha^{*^2})]\sigma_\eta^2 \\ &= 0.344\end{aligned}$$

and

$$\mathsf{E}\left[(z_t - \alpha^* z_{t-1})\zeta_t\right] = [(\beta - \beta^*)(1 + \alpha^{*2}) - \alpha^*\alpha\beta]\sigma_\eta^2 = 0 \tag{18}$$

since $(\beta - \beta^*)(1 + \alpha^{*2}) = \alpha^*\alpha\beta$ from (13). This is a consequence of ALS(1) being consistent for $(\alpha^*,\ \beta^*)$, but not for $(\alpha,\ \beta)$. Therefore, although u_{1t} in M_1 follows a first order autoregressive process $u_{1t} = \alpha u_{1t-1} + w_t$ with w_t white noise, and z_t is strongly exogenous for β in the DGP, ALS estimation of M_1 is inconsistent. In fact, w_t despite being white noise is not an innovation with respect to the information set including y_{t-1}, z_t, and z_{t-1}[5]:

$$\mathsf{E}\left[y_{t-1}w_t\right] = \alpha\beta^2\sigma_\eta^2 \quad \mathsf{E}\left[z_t w_t\right] = 0 \quad \mathsf{E}\left[z_{t-1}w_t\right] = \alpha\beta\sigma_\eta^2.$$

On the other hand, although ζ_t has a smaller variance than w_t, and is orthogonal to $(z_t - \alpha^* z_{t-1})$, it is not an innovation with respect to y_{t-1}, z_t, and z_{t-1}:

$$\begin{aligned}\mathsf{E}\left[y_{t-1}\zeta_t\right] &= (\alpha - \alpha^*)V(y) + \alpha^*\beta^*\beta\sigma_\eta^2 \\ \mathsf{E}\left[z_t\zeta_t\right] &= (\beta - \beta*)\sigma_\eta^2 \\ \mathsf{E}\left[z_{t-1}\zeta_t\right] &= [(\alpha - \alpha^*)\beta + \alpha^*\beta*]\sigma_\eta^2.\end{aligned}$$

Further, noting that ζ_t is ϵ_{2t} with α_2 and β_2 replaced by the pseudo true values of their ALS(1) estimators, it is clear from (17) that ζ_t and hence ϵ_{2t} are serially correlated.

[5] Granger (1983) contains an illuminating discussion of the difference between white noise and innovation random variables.

2.3.2 Sequential Reductions of M_4.

An alternative testing procedure uses the fact that the models form ordered nests within M_4, which is in fact over-parameterized relative to the DGP. The Incremental Tests in Figure 1 involve the test statistics for the sequence of hypotheses: (i) $(\mathsf{M}_3\mathcal{E}_p\mathsf{M}_4)$ and $(\mathsf{M}_1\mathcal{E}_p\mathsf{M}_3)$ and (ii) $(\mathsf{M}_2\mathcal{E}_p\mathsf{M}_4)$ and $(\mathsf{M}_1\mathcal{E}_p\mathsf{M}_2)$. These test statistics reveal that the sequential reduction $\mathsf{M}_4 \to \mathsf{M}_3$ is not rejected, but that the further reduction $\mathsf{M}_3 \to \mathsf{M}_1$ is strongly rejected. On the other hand the reduction $\mathsf{M}_4 \to \mathsf{M}_2$ is strongly rejected and so the further reduction $\mathsf{M}_2 \to \mathsf{M}_1$ is not relevant. In fact, given that $\mathsf{M}_4\mathcal{E}_p\mathsf{M}_2$ is rejected so that M_2 is not congruent, the test of $\mathsf{M}_1\mathcal{E}_p\mathsf{M}_2$ is invalid. However, despite M_2 being noncongruent, $\beta^* = \beta$ when $\alpha^* = 0$ from (12) and (13) so that under M_2 with $\alpha^* = 0$ the $\text{plim}_{T\to\infty}\,\hat{\beta}_1 = \beta$ which is consistent with a nesting model always encompassing a model nested within it - $\mathsf{M}_2\mathcal{E}\mathsf{M}_1$ in this case. Therefore, the incremental tests also perform well for this example, leading to M_3 as the simplest non-rejected reduction of M_4.

The only models listed above that will yield consistent estimates of β are M_1, M_3 and M_4. However, M_1 has serially correlated errors, is variance dominated by both M_3 and M_4, and $\mathsf{M}_3\mathcal{E}_p\mathsf{M}_4$. Therefore, the most efficient estimate of β comes from M_3. These theoretical results are closely matched by the sample statistics and the Monte Carlo simulation results reported in Table 3. The figures reported under the heading Monte Carlo are the average across 10,000 replications of the values of the calculated statistics associated with the estimation of the models. In fact, for M_1, M_3 and M_4 the Monte Carlo estimates are extremely close to the population values for all statistics. The same is true for M_2, except for the estimator of α_2 where there is evidence in the sample and the Monte Carlo estimates of the small sample Hurwicz (1950) bias $(-\frac{2\alpha}{T} = -0.01)$. Hence there is close agreement between the asymptotic theory, the sample estimates ($T = 100$), and the Monte Carlo estimates, for the particular point in parameter space represented by (1) and (2).

3 The Structure of Common Factor Restrictions.

Given the results in the previous section showing that inconsistent parameter estimates, and misleading inferences generally, can result from imposing invalid common factor restrictions, this section analyses the nature of these restrictions for general stationary processes in order to assess how likely it is that they will be valid in practice.

Consider a stationary ergodic process $\{\mathbf{x}_t\}$ for which $\mathbf{x}'_t = (y_t, \mathbf{z}'_t)$ with $\mathbf{z}_t$ a $k \times 1$ vector, and without loss of generality let $\mathsf{E}[\mathbf{x}_t] = 0 \ \forall\ t$ and

$$\mathsf{E}[\mathbf{x}_t\mathbf{x}'_s] = \Omega(|_{t-s}|) = \begin{pmatrix} \Omega_{yy}(i) & \Omega_{yz}(i) \\ \Omega_{zy}(i) & \Omega_{zz}(i) \end{pmatrix} = \begin{pmatrix} \Omega_{xy}(i) & \Omega_{xz}(i) \end{pmatrix} \tag{19}$$

for $i = |t-s|$ so that:

$$\Omega(i)^{-1} = \begin{pmatrix} \Omega^{yy}(i) & \Omega^{yz}(i) \\ \Omega^{zy}(i) & \Omega^{zz}(i) \end{pmatrix} = \begin{pmatrix} \Omega^{xy}(i) & \Omega^{xz}(i) \end{pmatrix} \tag{20}$$

To simplify the subsequent analysis with a relatively unimportant loss of generality it is assumed that the $\{x_t\}$ process is first order Markov, so that $\mathsf{D}(\mathbf{x}_t|X_{t-1}) = \mathsf{D}(\mathbf{x}_t|\mathbf{x}_{t-1})$ when $X_{t-1} = (....\mathbf{x}_{-1}, \mathbf{x}_0, \mathbf{x}_1, ...\mathbf{x}_{t-1})$ and has the form:

$$\mathbf{x}_t|\mathbf{x}_{t-1} \sim \mathsf{N}\left(\Pi_{xx}\mathbf{x}_{t-1},\ \Sigma_{xx} \right) \tag{21}$$

with

$$\Pi_{xx} = \Omega_{xx}(1)\,\Omega_{xx}(0)^{-1} \tag{22}$$

and

$$\Sigma_{xx} = \Omega_{xx}(0) - \Omega_{xx}(1)\,\Omega_{xx}(0)^{-1}\,\Omega_{xx}(1) = \Omega_{xx}(0) - \Pi_{xx}\Omega_{xx}(0)\,\Pi'_{xx}. \tag{23}$$

Higher order systems could be transformed into this first order form by use of the companion form representation [see Hendry and Mizon (1993) for a recent example]. Further, $\mathsf{D}(\mathbf{x}_t|\mathbf{x}_{t-1})$ can be factored into $\mathsf{D}(y_t|\mathbf{z}_t, \mathbf{x}_{t-1}) \times \mathsf{D}(\mathbf{z}_t|\mathbf{x}_{t-1})$ when $\mathbf{x}'_t$ is partitioned into $(y_t, \mathbf{z}'_t)$ with Π_{xx} and Σ_{xx} being similarly partitioned. The corresponding densities are:

$$y_t|\mathbf{z}_t, \mathbf{x}_{t-1} \sim \mathsf{N}\left(\alpha y_{t-1} + \boldsymbol{\beta}'\mathbf{z}_t + \boldsymbol{\gamma}'\mathbf{z}_{t-1},\ \sigma^2 \right) \tag{24}$$

$$\mathbf{z}_t|\mathbf{x}_{t-1} \sim \mathsf{N}\left(\Pi_{yy}y_{t-1} + \Pi_{zz}\mathbf{z}_{t-1},\ \Sigma_{zz}\right) \tag{25}$$

with:

$$\alpha = \Pi_{yy} - \boldsymbol{\beta}'\Pi_{zy},\ \ \boldsymbol{\beta}' = \Sigma_{yz}\Sigma_{zz}^{-1},\ \ \boldsymbol{\gamma}' = \Pi_{yz} - \boldsymbol{\beta}'\Pi_{zz},\ \ \sigma^2 = \Sigma_{yy} - \boldsymbol{\beta}'\Sigma_{zz}\boldsymbol{\beta}$$

Let $\boldsymbol{\lambda}_1' = (\alpha,\ \boldsymbol{\beta}',\ \boldsymbol{\gamma}',\ \sigma^2)$ and $\boldsymbol{\lambda}_2' = (\Pi_{zy},\ vec\,(\Pi_{zz})',\ vech\,(\Sigma_{zz})')$. Then assuming that the parameters of interest $\boldsymbol{\psi}$ are solely functions of $\boldsymbol{\lambda}_1$ and that $\boldsymbol{\lambda}_1$ and $\boldsymbol{\lambda}_2$ are variation free, ensures that $\mathbf{z}_t$ is weakly exogenous for $\boldsymbol{\psi}$, and so efficient inference on $\boldsymbol{\psi}$ can be made from $\mathsf{D}(y_t|\mathbf{z}_t, \mathbf{x}_{t-1})$ alone [see Engle, Hendry and Richard (1983)]. The relationship between the parameters of the conditional model $\mathsf{D}(y_t|\mathbf{z}_t, \mathbf{x}_{t-1})$ and those of the underlying Markov process (or VAR) $\mathsf{D}\,(\mathbf{x}_t|\mathbf{x}_{t-1})$ is given by:

$$\boldsymbol{\beta} = \left[\Omega_{zz}(0) - \Omega_{zx}(1)\,\Omega^{xx}(0)\,\Omega_{xz}(1)\right]^{-1}\left[\Omega_{zy}(0) - \Omega_{zx}(1)\,\Omega^{xx}(0)\,\Omega_{xy}(1)\right] \qquad (26)$$

and:

$$\boldsymbol{\gamma}' = \boldsymbol{\delta}'\Omega_{xx}(1)\,\Omega^{xz}(0) = \boldsymbol{\delta}'\Pi_{xz} \qquad (27)$$

$$\alpha = \boldsymbol{\delta}'\Omega_{xx}(1)\,\Omega_{xx}(0)^{-1}\,\boldsymbol{\delta} = \boldsymbol{\Pi}_{yy} - \boldsymbol{\beta}'\Pi_{zy} = \boldsymbol{\delta}'\Pi_{xy} \qquad (28)$$

$$\sigma^2 = \boldsymbol{\delta}'\Sigma_{xx}\boldsymbol{\delta}$$

when $\boldsymbol{\delta}' = (1,\ -\boldsymbol{\beta}')$ so that $\boldsymbol{\beta}' = \boldsymbol{\delta}'P$ with $P' = (0,\ -I_k)$.

Therefore the dynamics of the conditional model $\mathsf{D}\,(y_t|\mathbf{z}_t, \mathbf{x}_{t-1})$ will be represented entirely by an autoregressive error process if and only if the following common factor hypothesis H_0 holds:

$$\mathsf{H}_0 : \boldsymbol{\gamma} + \alpha\boldsymbol{\beta} = \Pi_{xz}'\boldsymbol{\delta} + \boldsymbol{\beta}\Pi_{xy}'\boldsymbol{\delta} = \left[\Pi_{xz}' + \boldsymbol{\beta}\Pi_{xy}'\right]\boldsymbol{\delta} = 0 \qquad (29)$$

or:

$$\mathsf{H}_0 : Q'\Pi_{xx}'\boldsymbol{\delta} = 0 \qquad (30)$$

when $Q' = (I_k,\ P'\boldsymbol{\delta}) = (I_k,\ \boldsymbol{\beta})$. The fact that the common factor restrictions are nonlinear is reflected in the dependence of Q on $\boldsymbol{\delta}$, and hence $\boldsymbol{\beta}$. Although these necessary and sufficient conditions are nonlinear functions of the underlying parameters of the VAR model only (namely Π_{xx} and Σ_{xx}) they cannot be written as simpler functions of them. However, a number of sets of sufficient conditions are easily obtained.

Sufficient Conditions for H_0 :

(i) $\Pi_{xx} = 0$ so that there are no dynamics in the system, and the common factors correspond to zero roots in the system.

(ii) $\Pi_{xx}\boldsymbol{\delta} = (\Pi'_{xz}\boldsymbol{\delta},\, \Pi'_{xy}\boldsymbol{\delta}) = 0$. This restriction is identical to $\boldsymbol{\gamma} = 0$ and $\alpha = 0$, so that there are no dynamics in the conditional model, and the common factors correspond to zero roots in the conditional model $\mathsf{D}\left(y_t|\mathbf{z}_t, y_{t-1}, \mathbf{z}_{t-1}\right)$.

(iii) $\Pi_{xx} = \Pi_{yy} I_n$ when $n = k + 1$. This means that y and $\mathbf{z}$ are mutually Granger-noncausal and that $\mathbf{z}_t$ has essentially the same temporal structure as y_t, since $\Pi_{xx} = \Omega_{xx}(1)\,\Omega_{xx}(0)^{-1} = \Pi_{yy} I_n$ implies that $\Omega_{xx}(1) = \Pi_{yy}\Omega_{xx}(0)$ and all the variables are mutually Granger-noncausal — see Spanos (1988).

(iv) $\boldsymbol{\delta}' = (1,0)$ and $\Pi_{yz} = 0$ which implies that $\boldsymbol{\beta} = 0$ and $\boldsymbol{\gamma} = 0$. In this case $Q'\Pi'_{xx}\boldsymbol{\delta} = Q'\Pi'_{yx} = \Pi'_{yz} = 0$, so that y_t is unrelated to $\mathbf{z}_t$ or its lags, though y can still Granger-cause $\mathbf{z}_t$. The particularly restrictive nature of this model is seen by noting that the VAR takes the following form in this case:

$$\begin{pmatrix} y_t \\ \mathbf{z}_t \end{pmatrix} = \begin{pmatrix} \Pi_{yy} & 0 \\ \Pi_{zy} & \Pi_{zz} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ \mathbf{z}_{t-1} \end{pmatrix} + \begin{pmatrix} v_{1t} \\ \boldsymbol{\nu}_{2t} \end{pmatrix} \tag{31}$$

with

$$\begin{pmatrix} v_{1t} \\ \boldsymbol{\nu}_{2t} \end{pmatrix} \sim \mathsf{NI}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \Sigma_{yy} & 0 \\ 0 & \Sigma_{zz} \end{pmatrix} \right) \tag{32}$$

Hence y_t is generated by a purely autoregressive process, unaffected by the process generating $\mathbf{z}_t$, though it can Granger-cause $\mathbf{z}_t$.

For economic time series each of these sets of sufficient conditions is very restrictive and unlikely to hold in practice. Indeed, it does seem that for linear stationary ergodic systems the common factor restriction embodied in H_0 is nothing more than a 'convenient simplification' when it is valid — see Hendry and Mizon (1978). However, many of the points made above about the adverse consequences of imposing invalid common factor restrictions still apply for non-stationary systems. In addition, since many economic time series are now analyzed within an integrated-cointegrated framework, the next section contains comments on common factor restrictions in such systems.

4 Common Factor Restrictions in Integrated Systems.

Following the influential work of Box and Jenkins (1970) and Granger and Newbold (1974) much more attention was paid to the time series properties of data by econometricians. In particular, the possibility that a nonstationary variable might be rendered stationary by a difference transformation was, and still is, often exploited. Hendry and Mizon (1978) pointed out such difference transformations in a multivariate context are particular examples of common factor restrictions, and argued the case for testing the validity of these restrictions rather than imposing them untested. Their further argument, that differencing variables prior to modelling the relationship between them means that potentially valuable long run or zero frequency information is ignored, was strengthened greatly by Granger's proposal of the concept of cointegration [see Granger (1981) and Engle and Granger (1987)]. There is now an enormous and growing literature on integration and cointegration - Banerjee *et al* (1993) provide an excellent review of it. The importance of the analysis of integration and cointegration in both theoretical and applied econometrics, justifies drawing attention to the consequences of imposing invalid common factor restrictions in this context and especially in the testing for unit roots.

4.1 Univariate Unit Roots

When y_t and $\mathbf{z}_t$ are $\mathsf{I}(1)$ the relationship $y_t = \boldsymbol{\beta}'\mathbf{z}_t + u_t$ will only have an error u_t which is $\mathsf{I}(0)$ if y_t and $\mathbf{z}_t$ cointegrate. A common test for cointegration between y_t and $\mathbf{z}_t$ is to test whether the OLS residuals:

$$\hat{u}_t = y_t - \hat{\boldsymbol{\beta}}'\mathbf{z}_t \tag{33}$$

have a unit root - the hypothesis of cointegration being rejected if the unit root hypothesis is not rejected. Perhaps the most popular univariate unit root test procedure is that due to Dickey and Fuller (1979, 1981) in which the regression

$$\Delta\hat{u}_t = \delta\hat{u}_{t-1} + \xi_t \tag{34}$$

is used to test the hypothesis $\delta = 0$ by comparing the $t_{(\delta=0)}$ statistic with critical values from the Dickey-Fuller distribution. Note that (33) and (34), with $\hat{\boldsymbol{\beta}}$ replaced by $\boldsymbol{\beta}$, imply:

$$\Delta y_t = \boldsymbol{\beta}'\Delta\mathbf{z}_t + \delta(y_{t-1} - \boldsymbol{\beta}'\mathbf{z}_{t-1}) + \xi*_t \tag{35}$$

which can be rearranged as:

$$y_t = (1+\delta)y_{t-1} + \boldsymbol{\beta}'(\mathbf{z}_t - (1+\delta)\mathbf{z}_{t-1}) + \xi*_t \tag{36}$$

from which it is clear that (36) has a common factor of $[1-(1+\delta)L]$. Thus the Dickey-Fuller (DF) and the various forms of Augmented DF test procedures impose an untested common factor and then test whether this common factor has a unit root. Not surprisingly, this procedure has been shown to lack power when the common factor restriction is invalid [see Kremers *et al* (1992)]. A further complication with the DF and ADF procedures arises from their use of two-stage estimation: (i) OLS estimation of $\boldsymbol{\beta}$ assuming that $\delta = 0$; followed by (ii) OLS estimation of δ conditional on $\boldsymbol{\beta} = \hat{\boldsymbol{\beta}}$. Although the procedure is justified on the grounds that $\hat{\boldsymbol{\beta}}$ is super-consistent, this does not ensure good properties in small samples [see Banerjee *et al* (1986) and the further results in Banerjee *et al* (1993)].

An alternative test for cointegration between y_t and $\mathbf{z}_t$, which does not have these drawbacks, is based on the error correction model (ECM). Assuming for simplicity that a model with first order dynamics:

$$y_t = \alpha y_{t-1} + \boldsymbol{\beta}'\mathbf{z}_t + \boldsymbol{\gamma}'\mathbf{z}_{t-1} + \omega_t \tag{37}$$

provides an adequate representation of the relationship between y_t and $\mathbf{z}_t$, then a re-parameterization yields the ECM:

$$\Delta y_t = \boldsymbol{\beta}'\Delta\mathbf{z}_t - (1-\alpha)(y_{t-1} - \boldsymbol{\kappa}'\mathbf{z}_{t-1}) + \omega_t \tag{38}$$

when $\boldsymbol{\kappa} = (1-\alpha)^{-1}(\boldsymbol{\gamma}+\boldsymbol{\beta})$ is the long run static response of y to $\mathbf{z}$. Note that in general $\boldsymbol{\kappa}$ differs from $\boldsymbol{\beta}$ the instantaneous short run response of y_t to $\mathbf{z}_t$, since the common factor restriction $(\boldsymbol{\gamma}+\alpha\boldsymbol{\beta}) = \mathbf{0}$ has not been imposed. If y_t and $\mathbf{z}_t$ are cointegrated with cointegrating vector $(1, \ -\boldsymbol{\kappa})$ then $(y_{t-1} - \boldsymbol{\kappa}'\mathbf{z}_{t-1})$, Δy_t and $\Delta\mathbf{z}_t$

are all $\mathsf{I}(0)$, so that $\omega_t \sim \mathsf{I}(0)$ even with $\alpha \neq 1$. Kremers *et al* (1992), Banerjee *et al* (1993) and Campos *et al* (1993) each present theoretical and Monte Carlo results that imply that $t_{(c=0)}$ in the rearranged ECM:

$$\Delta y_t \;=\; \boldsymbol{\beta}'\Delta \mathbf{z}_t + c(y_{t-1} - \mathbf{z}_{t-1}) + \omega *_t \tag{39}$$

with $c = (\alpha - 1)$, $\omega_t * = \omega_t + c(\mathbf{i} - \boldsymbol{\kappa})'\mathbf{z}_{t-1}$ and $\mathbf{i}$ a $k \times 1$ vector of unit elements, is a preferable test of cointegration to the DF (ADF) $t_{(\delta=0)}$. In particular, $t_{(c=0)}$ has a distribution under the null of no cointegration (i.e. $c = 0$) which is well approximated by $\mathsf{N}(0,1)$, and under the alternative of cointegration has higher power than the DF (ADF) $t_{(\delta=0)}$ statistic provided that $\frac{c^2}{\sigma^2}(\mathbf{i} - \boldsymbol{\kappa})'\Sigma_{zz}(\mathbf{i} - \boldsymbol{\kappa})$ is sufficiently large. Campos *et al* (1993) conclude: 'When conditioning is valid, Dickey-Fuller statistics used to test for cointegration have no particular advantage over their ECM counterparts; and there is much to gain from using the latter when the common factor restriction is invalid'. Hence there are clear disadvantages to using univariate unit root test statistics that impose potentially invalid common factor restrictions - a point that applies more widely than just to the DF and ADF test statistics.

4.2 Multivariate Unit Roots

If in the n dimensional system (21) $\mathbf{x}_t \sim \mathsf{I}(1)$ then there are two important cases in which $\boldsymbol{\epsilon}_t \sim \mathsf{I}(0)$.

(i) $rank(\Pi_{xx} - I_n) = v < n(= k+1)$ so that the system has v cointegrating vectors and $(n - v)$ driving variables or common trends. In this case the system has $(n - v)$ unit roots and the ML procedure of Johansen (1988) provides a multivariate unit root test based on the ECM:

$$\Delta \mathbf{x}_t \;=\; (\Pi_{xx} - I_n)\mathbf{x}_{t-1} + \boldsymbol{\epsilon}_t \tag{40}$$

to determine the value of v, which thus does not impose a common factor of Δ on all variables but tests the validity of this representation.

(ii) If $v = 0$ then $\Pi_{xx} = I_n$ so that (21) becomes:

$$\Delta \mathbf{x}_t \;=\; \boldsymbol{\epsilon}_t \tag{41}$$

which means that $\mathbf{x}_t$ is a multivariate $\mathsf{I}(1)$ process with no cointegration. In such a system each variable has a common factor of Δ, and there are no stable relationships between the elements of $\mathbf{x}_t$. Note further that the conditional models derived from (41) will have Δ as a common factor. The fact that (41) is a restricted version of (40) and it implies that there are only stable relationships among the changes $\Delta\mathbf{x}_t$ and not among the levels $\mathbf{x}_t$, serves to illustrate the importance of testing common factor restrictions rather than imposing them in multivariate $\mathsf{I}(1)$ systems.

5 Conclusions.

There are a number of extremely important implications for econometric modelling to be drawn from the analysis of the simple example in this paper.

1. Although it is important to test for serial correlation in the residuals of econometric models, it is rarely appropriate to 'autocorrelation correct' in response to rejecting the hypothesis of zero serial correlation.

2. Re-estimating a linear regression model by ALS imposes common factor restrictions, and inconsistent parameter estimates will result when the common factor restrictions are invalid. In fact, the example in section 2 illustrates such inconsistency even when the regression errors follow a first order autoregressive process!

3. The common factor restrictions imply very stringent constraints on the temporal structure of the variables being modelled, and as such are unlikely to hold in general. However, it is an empirical issue as to whether they are valid and so they should be tested, either directly (e.g. by using the COMFAC option within PC-GIVE), or indirectly via some of the sufficient conditions for them to hold.

4. The practice of 'autocorrelation correction' is an example of specific-to-general modelling, and so the example presented in section 2 is a particular illustration of the weaknesses of this modelling strategy. In contrast, a general-to-specific modelling strategy, which starts from a general congruent model and then tests for valid reductions of it, works impressively well. The general model M_4 is congruent and is parsimoniously encompassed by M_3, which is the data generation process for $y_t|z_t, z_{t-1}, y_{t-1}$. However, the static regression model M_1 and the ALS model M_2 are rejected as re-

ductions of M_4 and M_3.[6]

5. An important feature of the analysis is that the congruent general models M_4 and M_3 successfully explain the properties of models that are reductions of them. This illustrates that specification testing [in the sense of Mizon (1977a,b)], which is an essential feature of general-to-specific modelling, is a valid and effective way of modelling. Since M_3 is the DGP for the conditional process $\mathsf{D}(y_t|z_t, x_{t-1})$ it is not surprising that it has these properties. However, the overspecified model M_4 (it includes the irrelevant regressor z_{t-1} in the conditional mean for y_t) correctly indicates that M_3 is a valid reduction, but that M_1 and M_2 are invalid reductions, of it. The weakness of the overspecified (but otherwise congruent) model M_4 is not invalid inferences, but lack of efficiency in making valid inferences. This points to the value of incremental testing when there is a sequence of nested hypotheses, especially when it is an ordered sequence.

6. Given the importance of having congruent general models to provide a valid statistical framework for modelling, it is reassuring to note that the misspecification tests or diagnostic checking of models adopted in the paper powerfully indicated the inadequacy of noncongruent models. In particular, the residuals from M_1 are revealed to be highly serially correlated.

7. The results obtained in the paper, using a sample of size 100 of artificially generated data for a very specific DGP, have been explained using asymptotic theory. In addition to explaining the inconsistency of ALS for the single sample of size 100, the asymptotic theory for each statistic was seen to be in close agreement with the behaviour of the average of 10,000 Monte Carlo replications for these statistics. This strengthens the argument that 'autocorrelation correction' will lead to inappropriate inferences, since generally it imposes invalid restrictions.

8. COMFAC issues also arise in the analysis of nonstationary time series variables. Indeed, many of the univariate unit root test procedures commonly used in testing for cointegration (e.g. DF and ADF tests) impose common factors, and thus lack power

[6]In earlier versions of the paper, a first order autoregressive model for y_t, and the two COMFAC regression models associated with the bi-quadratic nature of the residual sum of squares for the Cochrane-Orcutt estimator, were also shown to be rejected strongly against both M_4 and M_3.

against alternatives in which the common factor restrictions are invalid. Also the practice of applying filters to all variables prior to analyzing the relationship between them (e.g. differences) results in inefficient, and possibly inconsistent, inference when the implied common factor restrictions are invalid.

Hence, even for the simple example considered here, analysis of the relationship between the DGP and models of the data (both more general, and simpler, than the DGP) has yielded a number of valuable insights and proved to be especially rich in implications for econometric modelling.

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